Heterogeneous Spillover Index in Latin America*

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Abstract

We extend Diebold and Yilmaz (2011) measure of financial market spillovers accounting for Heterogeneous effects of weekly, monthly and six-monthly horizons in order to analyze the return and volatility spillovers among Latin America's Stock markets and the United States, namely Argentina, Brazil, Chile and Mexico. The results indicate that the Heterogeneous extension closely tracks the spillover index showing higher connectedness. The model produces volatility spillovers with jumps in fragile periods and Return spillovers evolving gradually, as is documented in the vast literature while using simple computations. After the bankruptcy of Lehman Brothers however, return spillovers experience clear bursts similar to volatilities spillovers that are not documented in previous works.

Keywords: Vector Autoregression, Heterogeneous Autoregressive Models, Range, Volatility, Spillover Effects, Emerging volatility.

* The views expressed in this article do not necessarily reflect the views of the Superintendence of Banks, Dominican Republic.

Introduction

The Great Recession that affected the United States and Europe did not immediately cause contractions in emerging markets, particularly for the so called BRICs (Brazil, Rusia, India, China, and other emerging nations) that remained experiencing high growth rates. Terms such as "decoupling" and even "re-coupling" became popular as the traditional view of the connectedness among growth rates, and other indicators, came into scrutiny.

Such debates based on the interconnectedness and globalist nature of the present cast a question to academics among many social fields. In the economic literature there are conceptual differences on the causation dynamics of inter-connectedness, usually differenced between contagion and spillover effects. Also, the transmission channels that allow such supra national effects to spread can be broad and not necessarily evident.

Dornbusch et al. (2001) provide a review of two types of contagions, one developed by market economies inter-dependence such as growth rates, trade, investment and other "economic fundamentals", and another by "investor's behavior", such as bank lending, portfolio selection, institutional leveraged and speculative vehicles, and others.

The same authors seem to reserve the term "spillovers" for events such as currency crisis, changes in volatility and co-movement in capital flows and rate of returns. Pericoli and Sbracia (2003) further distinguish between a spillover that measures joint co-movements, and a more strict measure that accounts for such co-movements only when not explained by "fundamentals".

In this paper we are concerned about measuring linkages only thorough financial channels, namely of National Stock Markets in the Latin American region. We assume the linkages as spillovers. We would always have spillovers, regardless if they are explained by fundamentals or not, because statistically we use a variability component that can explain changes on one stock market because of another, making it invariant to a contagion measure.

When we refer to spillover effects we borrow from Pericoli and Sbracia (2003):

> *"Contagion occurs when volatility of asset prices spills over from the crisis country to the other countries"*

The continuation of idiosyncratic events reflected on the stock markets within a region or country upon another can be viewed as a form of financial spillover as it is caused by foreign forces.

It is important to emphasize that in times of tranquility or in the times whether a crisis in Thailand is spreading into East Asia, or a European Crisis threatens to spread over International Markets, stock returns and their volatilities have an inherent component that depends upon international factors. There is a need to better understand such "spillover effects".

From an investor perspective it is important to measure spillovers because it has implications to asset allocation during crisis and international events. For example, identifying which national stock markets are less susceptible to new crisis, can further aid in hedging a well-diversified portfolio of international assets. Schinasi and Smith (1999) point out that because of the VaR models used by commercial banks, it might become optimal for financial institutions to sell almost all of their high risk assets even when an adverse shock has only affected a fraction of uncorrelated high risk assets held in the portfolio.

For financial authorities and researchers it pays to understand, describe and monitor certain causation dynamics among international stock markets, as it improves evaluating and creating informed responses to reduce contagion. For example, it is argued that a decisive response by American authorities in the so called "Tequila Crisis" of 1994 limited the spillover effects from Mexico to the United States and other countries in the Americas whereas for the case of the Asian Crisis of 1997, that not understanding the possible contagion effects might have aided in not devising good enough policy solutions on the part of national and multilateral bodies.

Finally, it is very important for local authorities to understand what kind of actions and/or policy implementations are likely to accentuate spillovers in turbulent times, rather than limit them.

At this point we present a note on the related methodology used to measure spillover effects with regards to stock markets. In order to measure and forecast the riskiness in financial markets, it is essential to estimate assets returns, their variance and correlations with others. It is well known that volatility and co-movements in national stock markets are time varying and become more pronounced in periods of crisis (Engle 2002).

A way to measure the connectedness within financial markets is to see how returns and return volatilities are transmitted within and among regions. Popular methods for estimating volatility spillovers are employed from AutoRegressive Conditional Heteroskedasticity (ARCH) family models, or by monitoring the implied volatility (Gray and Malone, 2008) using option valuation models, among others. On the other hand, for the case to estimate return spillovers which are not serially correlated, Vector Auto Regression (VAR) are usually employed.

Focusing on modeling volatility via multivariate generalized ARCH models, Susmel and Engle (1990), Lin, Engle and Ito (1994), Karolyi (1995), Caporale et al. (2000), Luca, Genton and Loperfido (2007), Beirne et al. (2009) among others measured financial spillovers. As an alternative approach, Diebold and Yilmaz (2011) recently use the variance decomposition of a VAR to create a spillover index. In this respect the latter work uses a model free approach that is relatively easy to implement, and is equally employed for both return and volatility spillovers.

The present paper expands the latter approach to account for the heterogeneous effects of weekly, monthly and six-monthly horizons, describing return and volatilities spillovers of Financial Markets for Latin America. Volatility estimation and forecasting can be improved by employing such methods based in the different timing needs of market participants. The Heterogeneous Auto Regressive (HAR) model of Corsi (2009) can approximate long memory, a very important feature of volatility, while saving on parameters and computations. In this regard, extending a VAR into a Heterogeneous VAR with such properties could help enrich the model further while retaining its simplicity.

The organization of this paper is as follows. Section 2 reports a literature review on the stylized facts of Stock markets in Latin America. Section 3 presents the Heterogeneous VAR for obtaining the spillover index. Section 4 shows the empirical results, and Section 5 gives concluding remarks.

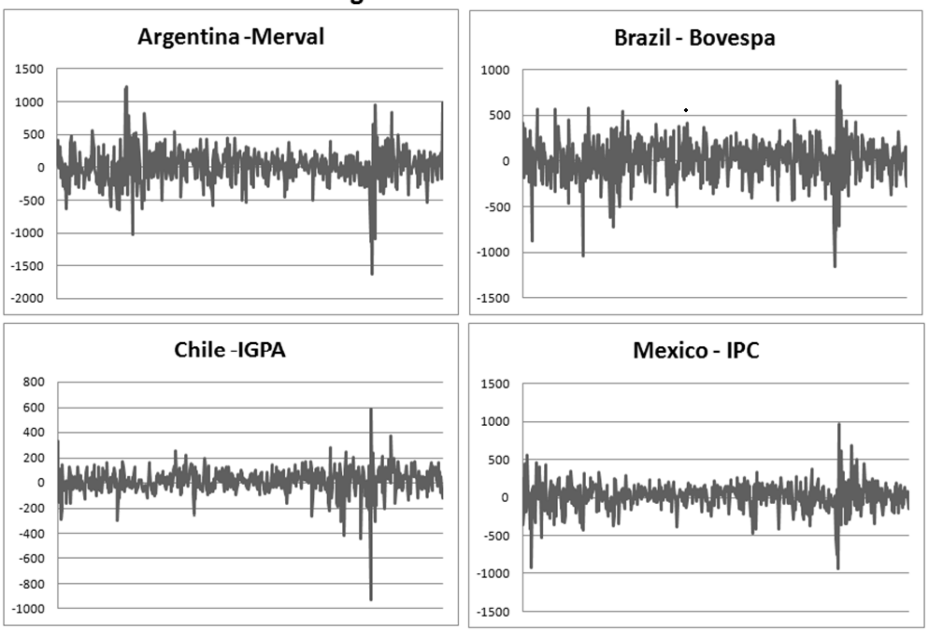
II. Stock return and volatility spillovers in Emerging Markets and Latin American Financial Markets

There are several distinctions among financial markets given by their characteristics and the relationships of their linkages. A vast literature investigates differences between emerging financial markets that experience higher returns and autocorrelations, as compared with major financial centers. In a sense, they tried to improve the predictability of returns.

As more developed financial markets are more integrated in the world economy and/or their equities are more liquid and transferable, they experience higher correlations with global events. In the cases for Latin America, Mexico and Brazil have experienced similar levels of correlation with global events; See Bora et al. (2009) and Bekaert and Harvey (2000), and Bekaert, Harvey and Ng (2005). But overall emerging market idiosyncratic risk is more susceptible to local, rather than regional and/or global events.

Besides return and autocorrelations, volatility is also higher in emerging markets. As can be seen in Figure 1 and 2, Argentina has observed the highest return and volatility (in the world) shocks for these ten years, which became especially obvious after its bond default in 2002.

Fig. 1 : Stock Return Plots

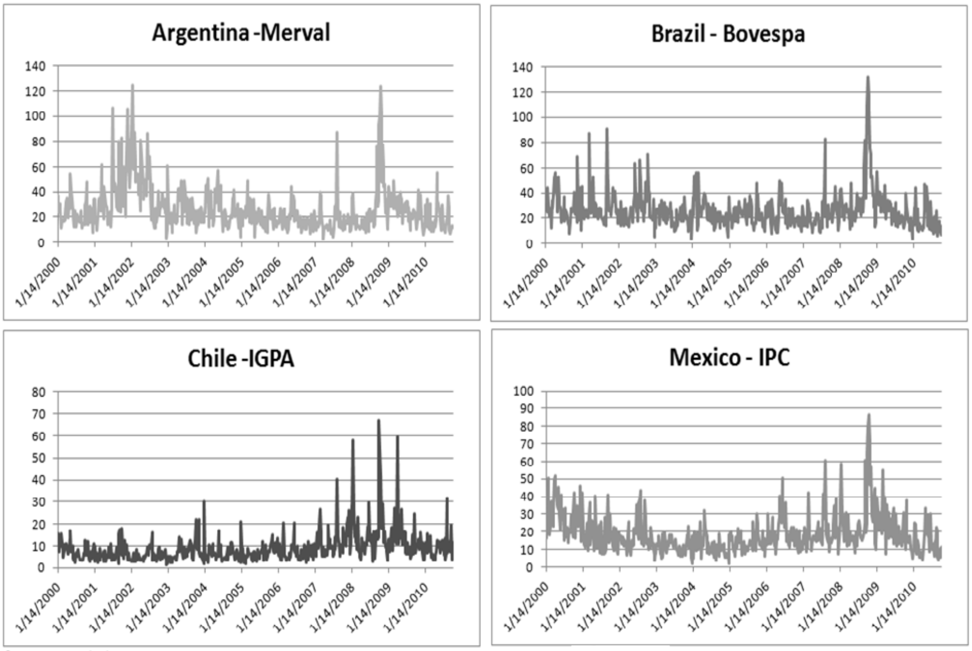


Data starts in January 2000, ends October 2010, including 563 weekly observations.

Emerging market volatility is more sensible to liberalizations (exchange rate, trade barriers) where it's mean increases notably during and a while after such reforms, and to other political events; see Girard and Biswas (2007). Also it is more likely that volatility in asset returns could transmit to the local currency volatility; See also Chen, Firth and Rui (2002). Hunter (2006) show that Argentina, Chile and Mexico have not fully integrated into world markets despite having experienced numerous liberalizations.

In other respect, it is more obvious that trading volume is positively correlated with volatility in emerging markets, and the leverage/asymmetric effects, in a situation where volatility increases more when assets are losing value than when assets are gaining value, are smaller in emerging markets as documented by Poon and Granger (2003).

Fig. 2: Return Volatility Plots



In the next section, we develop the Heterogeneous Spillover Index from Diebold and Yilmaz (2011), in order to study connectedness in the region.

III. Measuring Spillovers

1. The Spillover Index

For each asset i ($i = 1, \ldots, N$), we consider shares of its forecast error variance coming from asset j for all $i \neq j$. As explained below, Diebold and Yilmaz (2011) employ these forecast error variance in order to develop their spillover index.

First, consider the simple example of a covariance stationary first-order two variable VAR,

$$x_t = \Phi x_{t-1} + \varepsilon_t,$$

where $\boldsymbol{x}_t = (x_{1t}, x_{2t})'$ and Φ is a 2x2 parameter matrix. $\boldsymbol{x}_t$ will be a vector of either returns or return volatilities. By covariance stationary, the moving average representation of the VAR exists and is given by

$$x_t = \Theta(L)\varepsilon_t,$$

where $\Theta(L)$= $(\mathbf{I} - \Phi L)^{-1}$, more conveniently expressed in its moving average representation:

$$x_t = \mathbf{A}(L)u_t,$$

where $\mathbf{A}(L) = \Theta(L)\mathrm{Q}_t^{-1}, \mathrm{u}_t = \mathrm{Q}_t\varepsilon_t, \mathrm{E}(\mathrm{u}_t, \mathrm{u}_t') = \mathbf{I}$, and $\mathrm{Q}_t^{-1}$is the unique lower-triangular Cholesky factor of the covariance matrix of ε_t.

Now, consider the 1-step-ahead forecasting. The optimal forecast is

$$x_{t+1,t} = \Phi x_t.$$

with corresponding 1-step-ahead error vector

$$\mathbf{e}_{t+1,t} = x_{t+1} - x_{t+1,t} = \mathbf{A}_0\mathrm{u}_{t+1} = \begin{bmatrix} a_{0,11} & a_{0,12} \\ a_{0,21} & a_{0,22} \end{bmatrix} \begin{bmatrix} u_{1,t+1} \\ u_{2,t+1} \end{bmatrix},$$

which has a covariance matrix

$$\mathrm{E}(\mathbf{e}_t, \mathbf{e}_t') = \mathbf{A}_0\mathbf{A}_0' \ .$$

The Variance decompositions allow us to split the forecast error variances of each variable into parts attributable to the various shocks. A fraction of the 1-step-ahead error variance in forecast for $\mathbf{x}_1$ is given by itself and any other $\mathbf{x}_2$ for $i, j = 1,2, i \neq j$. There are two possible spillovers in a two-variable example: x_{1t} shocks that affect the forecast error variance of x_{2t}, with relative contribution $\tilde{a}^2_{0,21} = [\tilde{a}^2_{0,21}/(a^2_{0,21} + a^2_{0,22})]$, and x_{2t} shocks that affect the forecast error variance of x_{1t}, with a relative contribution given by $\tilde{a}^2_{0,12} = [\tilde{a}^2_{0,21}/(a^2_{0,11} + a^2_{0,12})]$. For the case that a shock in x_{-1t} affect x_1 it is considered to be an idiosyncratic shock that is caused by its own series and not a spillover. It is possible to convert the total spillover to an index expressing it as a ratio of the sum of relative contributions to the forecast error variance, which is $(\tilde{a}^2_{0,11} + \tilde{a}^2_{0,12}) + (\tilde{a}^2_{0,21} + \tilde{a}^2_{0,22}) = 2.$ With the ratio expressed as a percent, the spillover index is:

$$S = \frac{\tilde{a}^2_{0,12} + \tilde{a}^2_{0,21}}{2} * 100.$$

Having illustrated the Spillover Index in a simple first-order two-variable case, it is a simple matter to generalize it to richer dynamic environments. For a p^{th}-order *N*-variable VAR (but still using 1-step-ahead forecasts) we immediately have:

$$S = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{a}^2_{0,ij}}{N} * 100.$$

And for general *h* step-ahead forecasts, we have

$$S = \frac{\sum_{k=0}^{h-1} \sum_{i,j=1, i \neq j}^{N} a^2_{k,ij}}{N} * 100.$$

2. A Heterogeneous Spillover Index

Diebold and Yilmaz (2011) work with weekly data for their analysis. In the case of the Heterogeneous VAR (HVAR), we consider the average of *h*-horizon in order to capture heterogeneous effects such as weekly (h=1), monthly (h=4) and 6-monthly (h=24). Following on the convention employed by Corsi (2009) for the Heterogeneous AR (HAR) model, let $(x_{t-1})_h$ denote the h-horizon average of past x_t, defined by

$$(x_{t-1})_h = \frac{x_{t-1} + x_{t-2} + \cdots + x_{t-h}}{h},$$

then we have the monthly average and the average of six months as $(x_{t-1})_4$ and $(x_{t-1})_{24}$, respectively.

With this notation, the Heterogeneous VAR model is defined by

$$x_t = c + \Phi^w x_{t-1} + \Phi^m (x_{t-1})^4 + \Phi^s (x_{t-1})^{24} + u_t,$$

where $E(u_t|I_{t-1}) = 0$ and $V(u_t|I_{t-1}) = \Sigma_u$. It is a simple extension of HAR model of Corsi (2009).

In the case of the Heterogeneous VAR the model, the relationship to conventional VAR is given by

$$x_t = c + \left(\Phi^w + \frac{1}{4}\Phi^m + \frac{1}{24}\Phi^s \right) x_{t-1}$$

$$+ \left(\frac{1}{4}\Phi^m + \frac{1}{24}\Phi^s\right) x_{t-2} + \cdots \left(\frac{1}{4}\Phi^m + \frac{1}{24}\Phi^s\right) x_{t-4}$$

$$+ \frac{1}{24}\Phi^s x_{t-5} + \cdots + \frac{1}{24}\Phi^s x_{t-24}$$

The HVAR is expected to approximate long memory better than the VAR(p). Thus, HVAR is an approximated Long Memory model that is straightforward to implement compared to real long-memory models such as ARFIMA. One convenience of the HVAR compared to the VAR(24) is that we can have the properties of a high order VAR while saving on the parameters.

IV. Empirical Analysis of Spillovers in Latin America

1. Data

We examine stock market spillover index for both returns and return volatilities of four South American Stock Market Indexes: Argentina's Merval, Brazil's Bovespa, Chile's IGPA, and Mexico's IPC. The studied period lasts from January 2000 to October 2010 (563 weekly observations) obtained from finance.yahoo.com. We measure returns weekly, using underlying stock index levels at the last day of the week's close(whether it is Friday or not) and the first day of the week's open (whether it is Monday or not), and we express them as annualized percentages.

It is important to note that we first obtain the data daily and make the weekly calculations on our own. We also measure weekly return volatilities, using Garman and Klass (1980):

$$\tilde{\sigma}_{it}^2 = 0.511\,(H_{it} - L_{it})$$

$$-0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it}) - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2,$$

where *H*, *L*, *O* and *C*, are the week`s High, Low, Open and Close values respectively, expressed in logs.

Tables 1 and 2 show the summarized statistics for both returns and volatilities, respectively. And Figures 1 and 2 show their plots. These tables pick up the Argentinean crisis in 2001 and early 2002 that ended in a disorderly default on its debt. Also, most of the series show clearly a spike in both returns and volatilities after September 15 2008, the Fall of Lehman Brothers. Like Diebold and Yilmaz (2011), confirmed, volatilities are higher in Argentina and latter Brazil, while Chile experiences the least volatility among the Latin American countries.

Table 1: Return Summary Statistics

	Argentina	Brazil	Chile	Mexico
Mean	15.01148	13.48531	13.4704	14.48304
Standard Error	11.15498	9.340934	4.421024	7.581538
Medan	30.22138	31.14886	13.44807	28.82778
Standard Deviation	264.6811	221.6381	104.9004	179.8919
Sample Variance	70056.09	49123.46	11004.09	32361.08
Kurtosis	5.365982	3.116536	13.18092	4.632529
Skewness	-0.32578	-0.64189	-1.3191	-0.45544
Range	2857.332	2036.676	1501.382	1898.369
Minimum	-1621.43	-1160.87	-915.842	-932.281
Maximum	1235.901	875.8042	585.5406	966.0879
Sum	8451.463	7592.23	7583.836	8153.95
Count	563	563	563	563

Table 2: Volatility Summary Statistics

	Argentina	Brazil	Chile	Mexico
Mean	26.2794	26.16498	9.199313	18.76404
Standard Error	0.728609	0.607491	0.297293	0.46395
Median	21.7366	23.77133	7.404399	15.86985
Standard Deviation	17.28815	14.41431	7.054047	11.00842
Sample Variance	298.88	207.7724	49.75959	121.1853
Kurtosis	7.045846	12.57309	21.46758	6.038797
Skewness	2.251823	2.709835	3.780345	1.942445
Range	122.0662	128.9887	65.54966	84.69733
Minimum	2.611586	3.486083	1.30859	1.577886
Maximum	124.6778	132.4748	66.85825	86.27521
Sum	14795.3	14730.88	5179.213	10564.16
Count	563	563	563	563

2. Empirical Results

We compare both spillover indexes, one implemented with a VAR(2), 10 step-ahead forecasts and a 100 week rolling window, and the other called the “Heterogeneous Index” that instead of a VAR(2) uses an Heterogeneous VAR. Both models were estimated with the following Cholesky ordering: Argentina, Brazil, Chile and Mexico. Later we include the United States to study how its inclusion improves our analysis as it is important in the region. In that case the United States is ordered first and thereafter, the other countries in the same order.

Figure 1 show the stock return plots for all of the 563 observations in the four Latin American countries while Table 1 the respective descriptive statistics. Argentina surely shows higher extreme values, both in negative and positives annualized log returns, followed by Brazil and consequently Mexico. Chile shows the lowest variability in return plots at the lowest band.

On all four series the most important events occur after the Bankruptcy of Lehman Brothers where the return plots reach the most extreme values. In Argentina, the disorderedly default on its obligations that occurred on January 2002 seems almost as severe but not quite.

Figure 2 show the return volatility plots for Latin American countries. While for most of the period the annualized volatility of Chile remains around the 10% range, for the other Latin American countries it is clearly above 20%. Mexico is an exception averaging 18.76% during the period (see table 2). For all countries, volatilities start to increase considerably during 2007 when the problems of the US sub-prime market started to become apparent. The highest increases in volatility come with the "Leman Shock". Also, volatility in Argentina is as high during its own crisis in 2001-2002, as during the American crisis twice reaching 120% annually! Brazil makes the 120% mark only after the "Lehman Shock", Mexico and Chile reached their peaks at the same moment with 85% and 65% respectively. Table 2 shows the summary statistics for the volatilities.

(1) Return Spillovers without US

Next we proceed to show the results summarized in Table 3 and 4 which correspond to the return spillovers made with a VAR(2) and the Heterogeneous spillover index made with the HVAR. These tables include 440 observations captured in the rolling windows starting in 6/7/2002.

Table 3: Return Spillovers (w/o US)

	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	93.41	1.82	0.74	4.03	6.59
Brazil	72.28	22.97	1.42	3.33	77.03
Chile	53.36	2.37	43.65	0.63	56.35
Mexico	59.89	2.47	4.93	32.71	67.29
Contribution to others	185.52	6.66	7.1	7.98	207.26
Contribution including own	278.93	29.63	50.75	40.69	51.81 Spillover Index

In order to understand the tables better, it is important to see that the main diagonal of the tables tells us how much of the forecasted error variance of each series is caused by its own (idiosyncratic) shocks, as opposed to the (spillovers) shocks coming from the other series, totaled in the last column.

In this respect Table 3 shows that 93.41% of the forecasted error variance of Argentina, is attributed to shocks from Argentina (itself) and a total of 6.59% are due to shocks from the other 3 series, namely Brazil is contributing 1.82%, Chile 0.74% and Mexico 4.03%. Argentina is the country that causes the most spillovers in other series (first column), while Brazil is the country that causes the least spillovers to the others, and for whose contributions from others is the greatest (at 77.03 %).

Also, from the table we can easily see that the contribution to Argentina from Brazil (1.82%) is not the same as the contribution to Brazil from Argentina (72.28%), and so on. This is an example of a pair-wise level of connectedness that can express the relationships from, or to, of two of series. Empirically, it is a nice feature that allows us to infer a level of causation or sensibilities to financial contagion.

As a total measure of connectedness we have that the Spillover Index, i.e. the average of the total spillover to others (or from others) during the period, is 51.81 %.

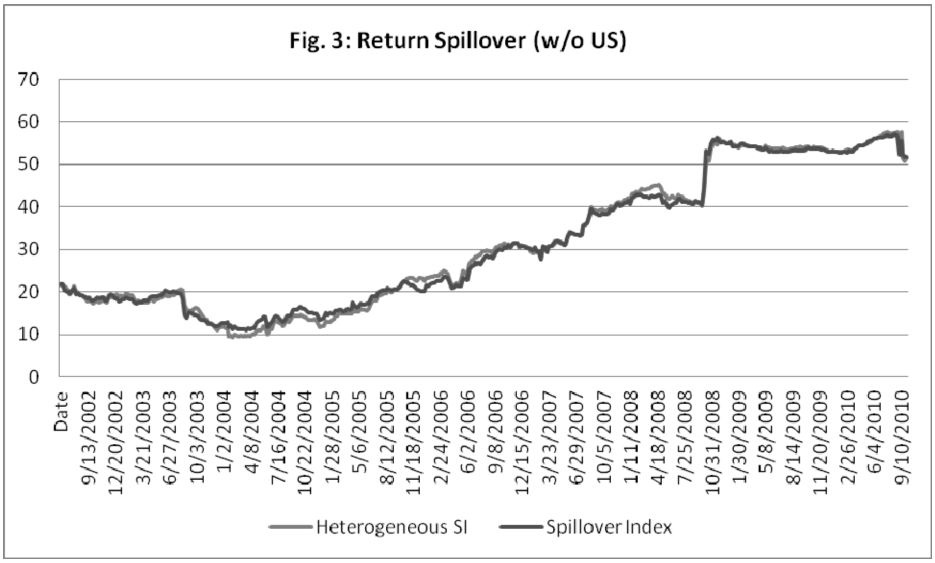
Table 4 shows the Heterogeneous Return Spillovers. Comparing it with the previous case explained above, the results appear to be quite similar. Something notable is that while spillovers from others are slightly smaller in this case, i.e. the series show less connections; Mexico is significantly more connected than before to all others.

Table 4: Heterogeneous Return Spillovers (w/o US)

	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	96.59	1.87	0.64	0.9	3.41
Brazil	72.71	24.41	1.29	1.6	75.59
Chile	49.62	3.45	45.88	1.05	54.12
Mexico	64.11	2.14	6.85	26.9	73.1
Contribution to others	186.44	7.45	8.78	3.55	206.22
Contribution including own	283.02	31.86	54.66	30.45	51.56 Heterogeneous SI

Next, more importantly than seeing the total averages of connectedness (Spillover Index) for the total period, it is more insightful to analyze how it changes over time (weekly) to identify relevant behavior going forward, and how the measure can relate to/explains known events. Figure 3 shows the evolution of both Indexes. Firstly, we note that return spillovers are generally continuous; secondly, they start at 20% and seem to tank at their lowest levels around 2004 (10% for Heterogeneous index) and later increase almost monotonically and gradually until they reach a plateau of 40% around May 2007 to September 2008, where high levels of uncertainty are apparent.

The “Lehman Shock” consequently elevates total connectedness to around 65% until June 2010 where it starts receding again.



(2) Return Spillover with US

Tables 5 and 6 show the two different models while including the United States in our analysis. As we mentioned before, including a country with important dynamics in the region and seeing if the model is accurate in perceiving such relations is important. Argentina used to contribute the most, but when the US is included, Argentina is only the highest contributor to others after the North American country; the spillover Indexes are higher showing more connectedness, but there are not considerable differences between the Heterogeneous and the Spillover index. In the particular case, we can see that the heterogeneous relationships in table 6 show that Argentina contributes slightly less to others (with the exception of Chile) than in the Spillover Index.

Also, when including the US, Mexico rather than Brazil is the country who receives the most spillovers from abroad for both indexes. This shows that using this methodology in the given period, the connection between Mexico and the US has a bigger importance to the region, than any bilateral connection between any two countries in Latin America.

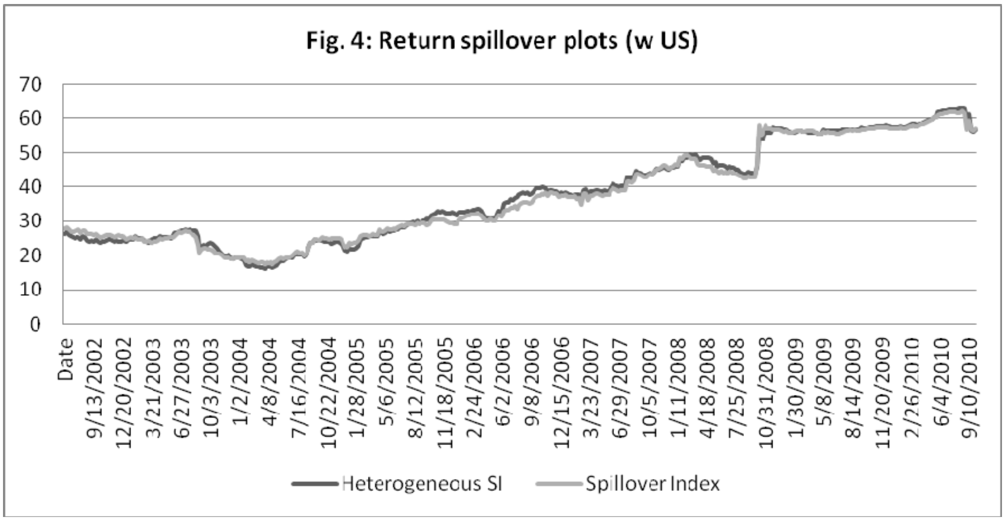
Table 5: Return Spillovers (w US)

	US	Argentina	Brazil	Chile	Mexico	Contribution from others
United States	85.30	10.72	0.13	1.65	2.20	14.70
Argentina	50.39	46.28	0.22	0.81	2.31	53.72
Brazil	55.23	21.68	20.38	1.73	0.97	79.62
Chile	42.64	12.85	0.69	41.64	2.19	58.36
Mexico	64.36	10.30	0.64	4.24	20.46	79.54
Contribution to others	212.62	55.55	1.68	8.43	7.66	285.94
Contribution including own	297.92	101.84	22.05	50.07	28.12	57.19 Spillover index

Table 6: Heterogeneous Return Spillovers (w US)

	US	Argentina	Brazil	Chile	Mexico	Contribution from others
United States	88.60	7.00	0.55	1.35	2.49	11.40
Argentina	48.53	45.21	0.34	1.19	4.72	54.79
Brazil	58.06	18.15	19.28	1.58	2.92	80.72
Chile	37.08	13.93	1.25	44.92	2.83	55.08
Mexico	68.38	7.87	0.99	4.27	18.50	81.50
Contribution to others	212.06	46.95	3.13	8.39	12.95	283.49
Contribution including own	300.66	92.17	22.42	53.31	31.45	56.70 HSI

Figure 4 show the Return Spillover plots when including the US for the two cases. When comparing Figures 3 and 4, there is simply a slight higher level of connectedness when including the US, otherwise both figures show very similar dynamics.



(3) Volatility Spillover without US

Next tables 7 and 8 show the Spillover and Heterogeneous Spillover Indexes for the volatility case. Again, Argentina is the country sending the most spillovers to others and Brazil the country that receives the most spillovers from others, even though it is closely tracked by Mexico. It is important to note that Chile behaves especially resilient to spillovers from abroad in both cases. For the general case, on average, volatilities experience lower connectedness than returns but vary in a less gradual, more discontinuous way.

Table 7: Volatility Spillovers in Latin America (w/o US)

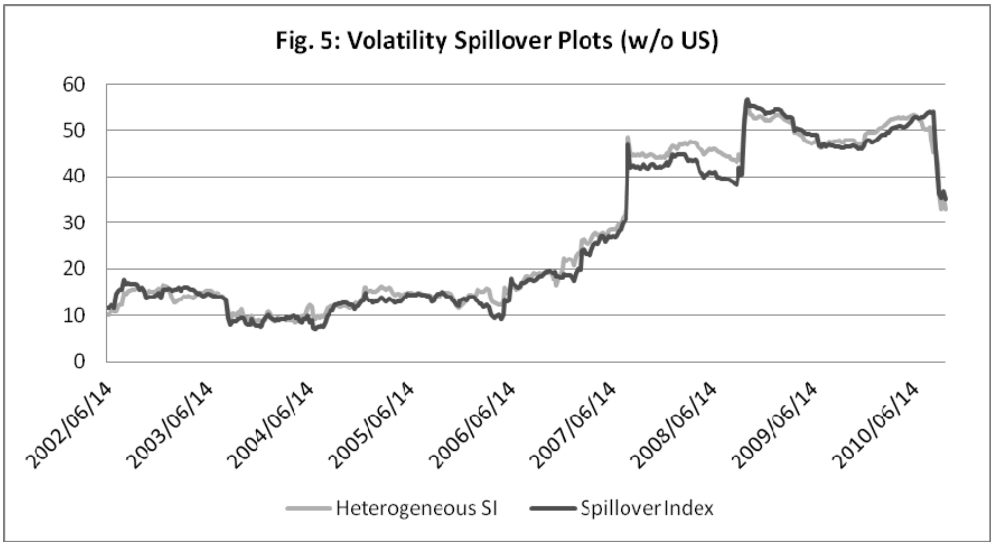
	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	92.82	5.2	1.51	0.46	7.18
Brazil	60.82	37.9	0.28	1	62.1
Chile	9.57	1.72	87.61	1.09	12.39
Mexico	46.03	12.13	2.81	39.03	60.97
Contribution to others	116.42	19.05	4.6	2.56	142.63
Contribution including own	209.24	56.95	92.22	41.59	35.66 Spillover Index

The Table 8 for the Heterogeneous volatility spillovers show slight differences to Table 7 when it comes to Mexico and Argentina. Argentina is contributing considerably less to Mexico, and consequently Mexico shows less contribution from Argentina.

Table 8: Heterogeneous Volatility in Latin America (w/o US)

	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	95.5	2.37	1.53	0.6	4.5
Brazil	59.55	38.79	0.88	0.78	61.21
Chile	6.74	3.25	87.77	2.23	12.23
Mexico	40.06	8.55	5.38	46.01	53.99
Contribution to others	106.35	14.18	7.79	3.61	131.93
Contribution including own	201.85	52.96	95.56	49.62	**32.98 HSI**

Figure 5 shows the Volatility Spillover plots for the two cases. They both show the heightened connectedness during 2007 and later the climax at the "Lehman Shock" in 2008. Comparing with returns, the differences are more pronounced and more detectable, especially in the periods of higher connectedness.



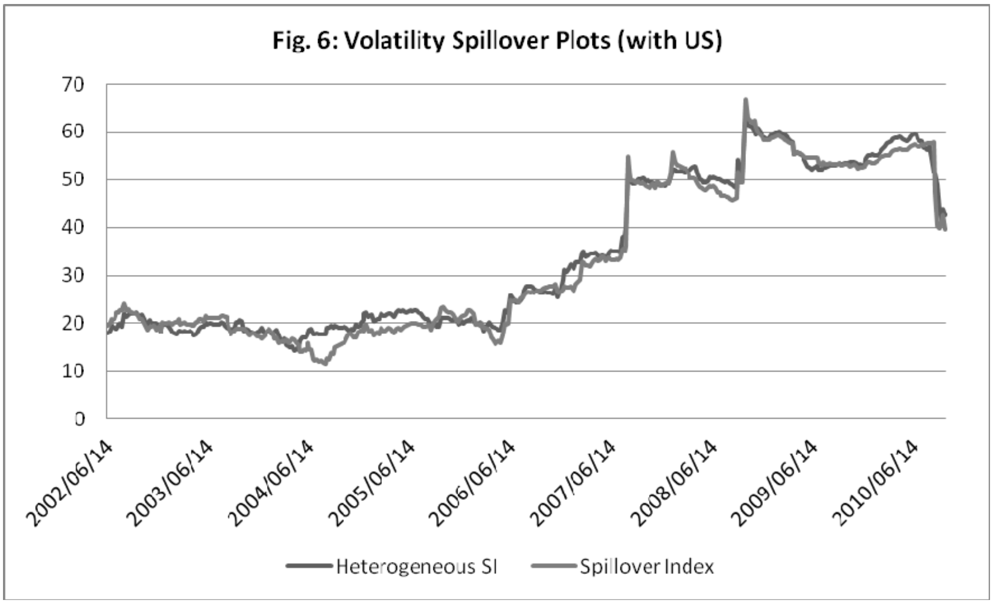
(4) Volatility Spillover with US

Finally, including the United States in the Volatility Spillovers, as can be seen in tables 9, and 10 for the Heterogeneous case, we see that the dynamics remains similar but the connectedness is generally higher; In the Heterogeneous case (table 9), the spillover index is slightly higher than in the original case. The US is contributing the most and Brazil is receiving the most spillovers.

Table 9: Volatility Spillovers (w US)

	US	Argentina	Brazil	Chile	Mexico	Contribution from others
United States	93.06	3.42	1.41	0.56	1.54	6.94
Argentina	39.85	55.07	2.62	1.74	0.73	44.93
Brazil	53.44	17.41	27.91	0.27	0.97	72.09
Chile	6.41	4.4	1.08	87.51	0.61	12.49
Mexico	53.91	8.72	2.53	3.01	31.83	68.17
Contribution to others	153.6	33.95	7.64	5.58	3.84	204.61
Contribution including own	246.66	89.03	35.55	93.08	35.68	40.92 Spillover Index

In Figure 6 that shows Spillover Indexes over time, a period in 2004 where both indexes appear to be negatively correlated can be appreciated. This might be caused to the different lags at forgetting the Argentinean crisis between the rolling window of the Heterogeneous model (that has a longer memory) and the vanilla VAR specification.



V. Concluding Remarks

We used Diebold and Yilmaz (2011) spillover index for Latin America, and compared it with an extension that uses a Heterogeneous VAR instead of a VAR(2) model. Both models can correctly describe the stylized facts of return and return volatilities for important countries in Latin America, namely Chile, Brazil, Mexico and Argentina. Also we analyze the countries relationship with the United States. The comparisons show that the Heterogeneous extension has slightly varying levels of connectedness (higher spillover index), and that return volatilities experience abrupt rather than a gradual changes after the “Lehman Shock” that was not documented in the previous works.

References

Beirne, J., G.M. Caporale, M. Schulze-Ghattas, and N. Spagnolo (2009), “Volatility spillovers and contagion from mature to emerging stock markets”,. International Monetary Fund WP08-286 and European Central Bank WP1113.

Bekaert, G. and C.R. Harvey (2000), “Foreign speculators and emerging equity markets”, Journal of Finance, 55, 565–613.

Bekaert G., Harvey C. and Ng A., (2005), “Market Integration and Contagion”, Journal of Business, 78, 39-69.

Bora, A. P. E. Mandaci, B. S. Kopurlu and B. Erqener (2009), “Behaviour of Emerging Stock Markets in the Global Financial Meltdown: Evidence from bric-a”, African Journal of Business Management 3, 396-404.

Caporale, G.M., A. Cipollini, and N. Spagnolo (2005), “Testing for Contagion: A Conditional Correlation Analysis.”, Journal of Empirical Finance, 12, 476–489.

Caporale, G.M., M. Chui, G.H. Stephen and H. Brian (2000), “Coordination and price shocks: an empirical analysis”, Economic Modelling, 18, 569-584.

Chen, G.-M., M. Firth and O.M. Rui (2002),”Stock Market Linkages: Evidence from Latin America”, In Journal of Banking and Finance, 26, 1113–1141.

Classens, S., R. Dornbusch, Y.C Park, Contagion: why crises spread and how this can be stopped International Financial Contagion, Kluwer Academic Publishing, Boston (2001), pp. 19−52

Corsi, F. (2009), “A Simple Approximate Long-Memory Model of Realized Volatility", Journal of Financial Econometrics, 7, 174-196.

Diebold, F.X. and K. Yilmaz (2011), “Equity Market Spillovers in the Americas,” in R. Alfaro(ed.) Financial Stability, Monetary Policy, and Central Banking. Santiago: Bank of Chile Central Banking Series, Volume 15, 199-214. (Published in Spanish as: Diebold, F.X. and Yilmaz, K. (2009), “Efectos de Derrame en Los Mercados de Valores del Continente Americano," Revista Economia Chilena, 12, 55-65.)

Engle, R. (2002), "Dynamic Conditional Correlation", Journal of Business and Economic Statistics, 20, 339-350.

Garman, M. B. and M. J. Klass (1980), "On the Estimation of the Security Price Volatilities from Historical Data", Journal of Business, 53, 67-78.

Girard, E., and R. Biswas (2007), "Trading volume and Market Volatility: Developed versus Emerging Stock Markets", The Financial Review, 42, 429–59.

Gray, D.F. and S.W. Malone (2008), Macro financial Risk Analysis, Chichester: John Wiley.

Hunter D.M. (2006), "The Evolution of Stock Market Integration in the Post-Liberalization Period – A look at Latin America", Journal of International Money and Finance, 25, 795-826.

Karolyi, G. A. (1995), "A Multivariate GARCH Model of International Transmissions of Stock Returns and Volatility: The Case of the United States and Canada", Journal of Business & Economic Statistics, 13, 11–25.

Lin, W., R. Engle and T. Ito (1994), "Do Bulls and Bears Move Across Borders? International Transmission of Stock Returns and Volatility", Review of Financial Studies, 7, 507–538.

Luca, G., M.G. Genton and N. Loperfido (2007), "A multivariate Skew-GARCH Model", in: D. Terrell and T.B. Fomby (eds), Econometric Analysis of Financial and Economic Time Series/Part A, Advances in Econometrics, Vol. 20, Bingley: Emerald Group Publishing Limited, 33-57.

Pericoli, M. and M. Sbracia (2003), "A Primer on Financial Contagion", Journal of Economic Surveys, 17,571-608.

Poon S.H. and C. W. Granger (2003), "Forecasting Volatility in Financial Markets: A Review", Journal of Economic Literature, 41, 478-539(62)

Susmel, R. and R.F. Engle (1990), "Hourly Volatility Spillovers between International Equity Markets", Working Paper. University of California, San Diego.

Appendix

In this section we re-estimate the previous models with a 200 rolling window instead of 100. The purpose is to compare and verify if the previous approach is the most appropriate for the measure.

When we used 100 rolling window we were able to plot 440 weekly observations for both the return and volatility spillover indexes. When we use a 200 rolling window, only 340 weekly observations can be plotted. Therefore, in this section spillover indexes will start from April 23, 2004 instead of June 7, 2002.

Generally speaking, using a 200 rolling window will make the plots less variable, as the bigger weight of past events will smoothen out newer events.

Particularly for the return spillovers, comparing tables 11 and 12 to tables 3 and 4 respectively we can see similar tendencies in events such as the Fall of Lehman Brothers and the steady buildup of connectedness from 2004, yet indexes computed with a 200 rolling window are smoother.

With regards to the internal dynamics, the plots in Figure 7 also remain relatively similar: Argentina is the country that contributes most to others, whereas now Mexico and not Brazil, is the country that receives the most spillovers from others. Overall the Heterogeneous model shows less connectedness as it does not increase as rapidly during the fall of Lehman Brothers.

When including the US, in tables 13 and 14, we can appreciate an overall lower level of connectedness as opposed to tables 5 and 6. Furthermore, it is now difficult to appreciate which country, Brazil or Mexico, is the one receiving the most contributions from others, accentuating the importance of the US causing events in Mexico's volatility. Other dynamics remain similar.

One important note when comparing Figure 4 and Figure 8 can be seen at the end of the plots, around June 2010. The former case can capture a decrease in overall connectedness faster than the latter. It shows that having a larger rolling window makes the model slower to appreciate new events, especially when a period of high stress is in the window. I believe this observation will further justify the implementation of the 100 rolling window.

For the case of volatility spillovers, we omitted the tables and figures in order to save spaces, and they are available upon request. In this case, again, a fact that stands out is around the end of the period in June 2010 that the 200 rolling window fails to appreciate that connectedness is decreasing whereas a 100 rolling window charts capture richer dynamics.

With respect to volatility spillovers, without including the US will tell us a similar story: Argentina is contributing the most and Mexico receiving the most volatility spillovers from others.

Figures and Tables for Appendix

Table 11: Return Spillover (w/o US)

	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	84.26	10.6	2.89	2.25	15.74
Brazil	57.15	40.9	0.69	1.21	59.05
Chile	33.41	12	54.2	0.42	45.8
Mexico	54.38	17.1	1.28	27.2	72.77
Contribution to others	144.94	39.69	4.86	3.87	193.37
Contribution including own	229.2	80.64	59.06	31.1	48.34 Spillover Index

Table 12: Heterogeneous Return Spillover (w/o US)

	Argentina	Brazil	Chile	Mexico	Contribution from others
Argentina	90.65	6.47	1.34	1.54	9.35
Brazil	61.53	37.22	0.34	0.91	62.78
Chile	35.11	9.26	55.16	0.47	44.84
Mexico	57.64	15.61	1.34	25.42	74.58
Contribution to others	154.27	31.34	3.03	2.92	191.56
Contribution including own	244.92	68.56	58.18	28.34	47.89 Spillover Index

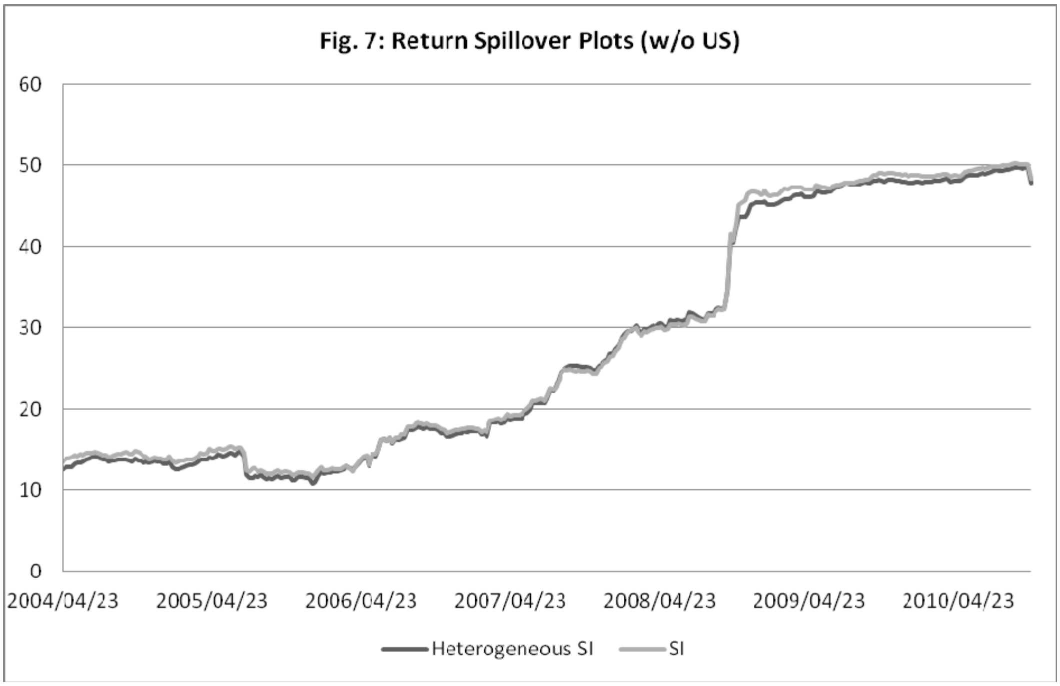


Table 13: Return Spillovers (w/US)

	US	Argentina	Brazil	Chile	Mexico	Contribution From others
United States	89.5	9.61	0.35	0.21	0.33	10.5
Argentina	42.51	52.33	1.76	2.28	1.12	47.67
Brazil	61.53	15.67	22.34	0.38	0.07	77.66
Chile	38.49	7.33	1.99	51.7	0.5	48.3
Mexico	62.83	13.94	1.86	0.44	20.93	79.07
Contribution to others	205.37	46.55	5.95	3.31	2.02	263.21
Contribution including own	294.87	98.88	28.29	55.01	22.95	52.64 Spillover index

Table 14: Heterogeneous Return Spillovers (w/ US)

	US	Argentina	Brazil	Chile	Mexico	Contribution From others
United States	89.27	7.42	1.03	0.84	1.45	10.73
Argentina	38.71	54.47	3.46	2.32	1.05	45.53
Brazil	59.34	15.23	22.39	0.95	2.08	77.61
Chile	38.74	5.39	1.96	53.05	0.85	46.95
Mexico	61.51	13.42	3.52	1.34	20.21	79.79
Contribution to others	198.3	41.46	9.97	5.45	5.43	260.61
Contribution including own	287.57	95.93	32.36	58.5	25.64	52.12 Spillover Index